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A Methodology For Sensitivity Analysis In Complex Distributed Watershed Models

Jennifer Benaman[2] and Christine Shoemaker[1]

[1] Joseph P. Ripley Professor, School of Civil and Environmental Engineering, Cornell University Ithaca, NY 14853, Ph.D. (ASCE Fellow), PH (607) 255-9233; FAX (607) 255-9004, cas12@cornell.edu
[2] Quantitative Environmental Analysis, LLC, 800 Brazos Street, Suite 1040, Austin, TX 78701, Ph.D. (ASCE Associate Member) jbenaman@qeallc.com

Abstract

Pollution transport models are based on field data and the calibration of the parameter values that cannot be directly measured. This combination of field data and calibrated model can provide an important investigative and planning tool in environmental analysis. However, the calibration process for such models can be computationally very demanding if it is done thoroughly. An even more serious computational burden is parameter sensitivity associated with models that have a large number of parameters. This paper discusses computationally efficient methods for sensitivity analysis. It also discusses applications to the large and highly significant Cannonsville watershed, which provides drinking water for New York City. The watershed model used is SWAT. The sensitivity analysis method is applied to 160 parameters simultaneously. The methodology described can also be applied to other types of models arising in water resources and in hydraulics.

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Introduction

Calibration and sensitivity analysis of watershed models is an essential component of planning for long-term, sustainable pollution control. We address in this paper the application of calibration and a new sensitivity analysis methodology to the Cannonsville watershed in New York State, U.S.A. This application can be used to illustrate the synergistic significance of computational efficiency of calibration and sensitivity analysis.

Regulatory standards for watersheds in the U.S. are based in part on Total Maximum Daily Loads (TMDL). As a result, the focus of water quality management for materials like phosphorous has moved from end of the pipe' or point source control to watershed scale analyses that incorporate point and non-point source pollution assessments. The synergy between water, sediment transport and phosphorous transport in the watershed result in interactions between parameters for all these substances in their effect on model output predictions. As a result site-specific calibration of the model is difficult. We will discuss a proposed methods for improved computational algorithms that can significantly improve our scientific ability to understand, analyze, and manage complex environmental systems.

Application To Cannonsville Watershed

The Cannonsville Reservoir in Delaware County, New York, is part of the New York City water supply system (Figure 1). The reservoir's 1178 km^2 has been designated "phosphorus restricted" by the New York City Watershed Memorandum Agreement (MOA). As a result, future development in the reservoir's watershed is restricted.

Available Data And Watershed Delineation

The Cannonsville Watershed is under careful control due to the current phosphorus load restriction imposed by New York City. As a result, a significant amount of data exists to aid in the development and calibration of a watershed model. In addition, because the watershed model is a distributed model, it requires spatial information to accurately simulate the system.

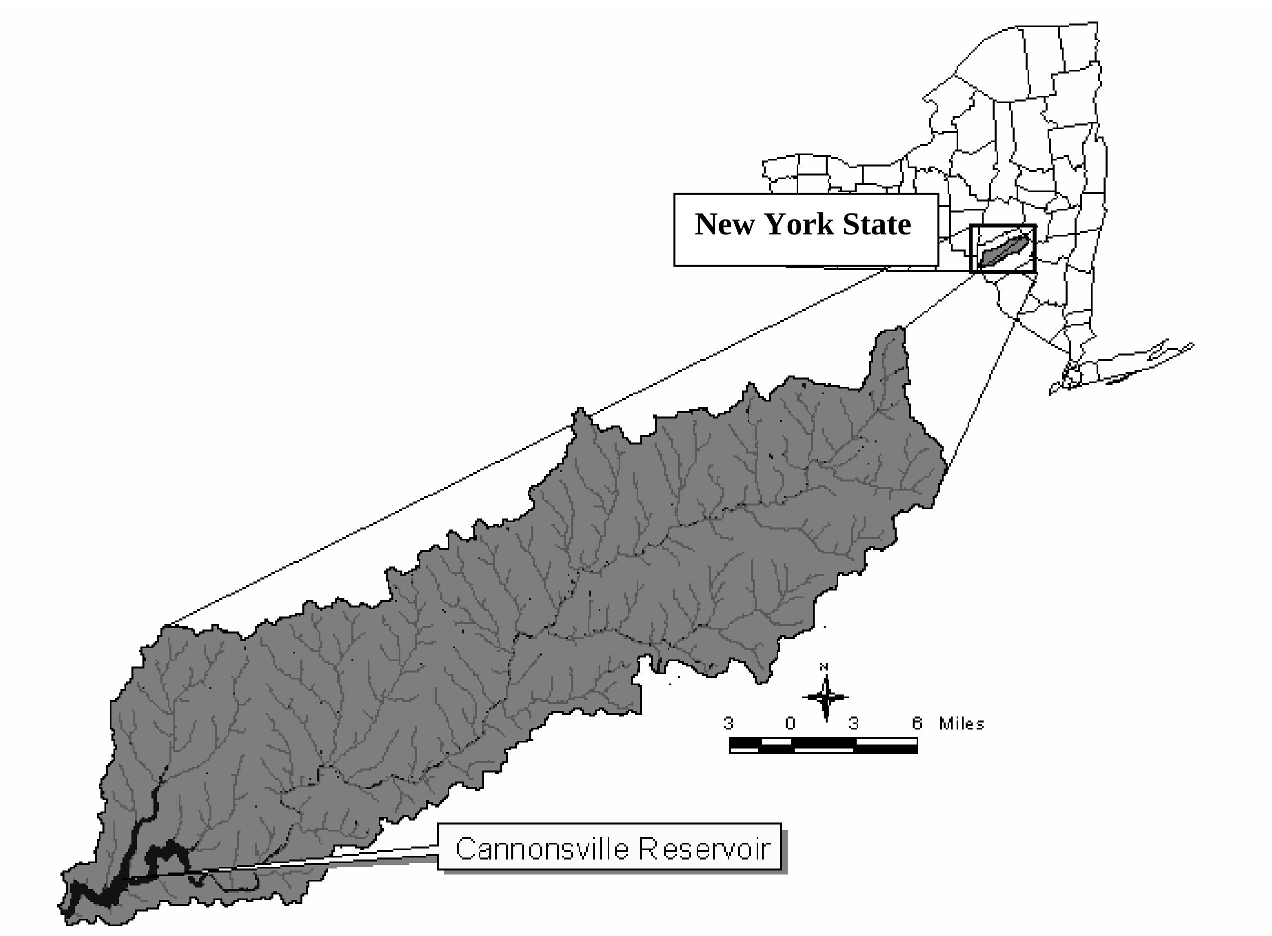

Figure 1. Cannonsville Watershed in New York State, U.S.A. (Reprinted with permission from Benaman, 2003)

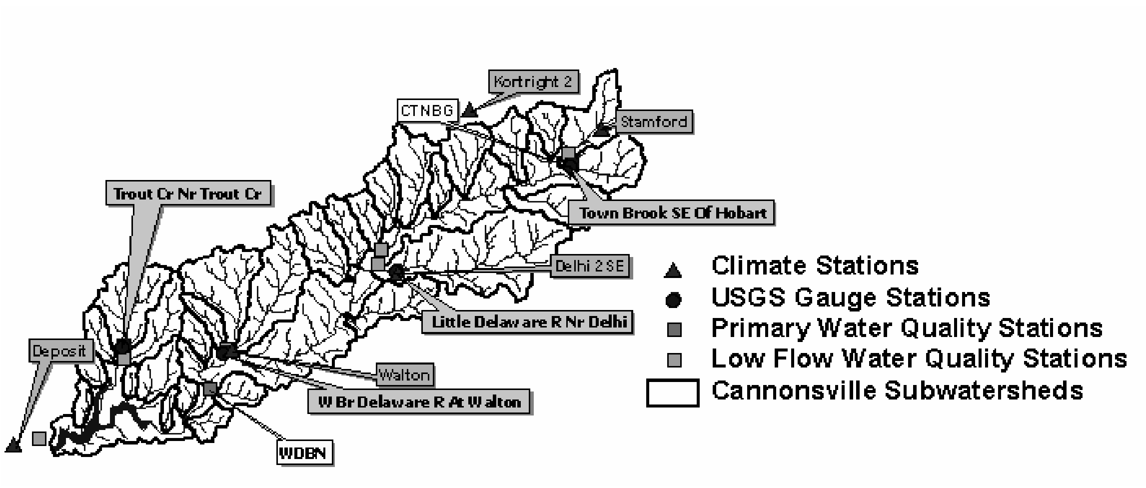

Figure 2 Cannonsville basin showing subwatersheds and monitoring gauge locations

Model Selection

We determined that the most appropriate model for this scale of watershed and for long-term analysis was the Soil and Water Assessment Tool (SWAT Version 2000). SWAT, a semi-distributed watershed model developed by the United State Department of Agriculture (USDA), has been applied throughout the United States (Cho et al. 1995; Bingner 1996; Arnold et al. 1998, 1999; Peterson and Hamlett 1998; Srinivasan et al. 1998; Arnold et al. 1999; Neitsch et al. 2001). The equations in SWAT focuses on a soil water balance. SWAT simulates the water balance, along with plant growth, sediment erosion and transport, nutrient dynamics, and pesticides. The model permits the incorporation of management practices on the land surface, including fertilizer application, livestock grazing, and harvesting operations. Neitsch (2001) details the full capabilities of the SWAT model.

There are hundreds of parameters in SWAT. Some of these parameters vary by subbasin, land use, or soil type, which increases the number of parameters substantially. Some of these parameters, such as hydraulic conductivity and soil bulk density, represent measurable quantities and hence can be estimated directly form field data. However, a good number of other parameters are empirical or SWAT-specific. For example, SWAT uses the Modified Universal Soil Loss Equation (MUSLE) to estimate soil erosion (Neitsch et al. 2001).

Calibration

The longest-running flow gage for the watershed drains approximately 80% of the watershed. This was the primary calibration location. In addition, there are gages located throughout the watershed that drain smaller subbasins and have shorter periods of record (~2 years). These were used during the calibration procedure. The flows were compared on a daily, monthly, seasonal, and annual basis to determine if there are trends in model output or error.

The response of the watershed can be assessed at varying spatial scales because SWAT is a spatially distributed model. The subwatersheds established for the SWAT application to the

Cannonsville watershed were established based on major tributaries entering the West Branch Delaware River, which is the main river within the basin, and Cannonsville Reservoir. These 31 basins (given in Figure 2) were identified with the aid of GIS using a digital elevation model and stream network (Neitsch and DiLuzio 1999). Each subbasin is partitioned into Hydrologic Response Units (**HRU**s) that are determined by unique intersections of the land use and soils within the basins. These HRUs are the spatial level at which the model computes the effect of management practices such as crop growth, fertilizer application, and livestock management. We established 301 HRUs for the entire basin, which is an average of 10 HRUs per subbasin

The results on calibration and validation of the SWAT model for the Cannonsville watershed are reported by Benaman et al. (2003) report . The goodness-of-fit measures included percent differences in averages and standard deviations over the simulation period, coefficient of correlations (R^2) and the Nash-Sutcliffe measure. All of these measures were calculated for all four flow gauges draining various subwatershed sizes. The monthly R^2 values range from 0.72 to 0.80, with the highest R^2 at the Walton station, which drains 80% of the watershed area. The percent difference in averages was 4% for the main discharge point at Walton

Sensitivity analysis

Benaman and Shoemaker (2003) developed a new methodology for sensitivity analysis method to deal with models with a large number of parameters. This method is designed to be both computationally efficient and robust for assessing individual sensitivity analysis. The robust nature of the sensitivity method is based on the use of multiple perturbation, sensitivity indices and output variables. One-hundred-sixty (160) SWAT parameters were chosen out of over 300 potential parameters for the sensitivity analysis. Among these 160 parameters, 35 were basin wide, 10 varied by land use (5 land uses = 50 parameters) and 7 varied by soil type (10 soil types = 70 parameters). There were also two parameters that were analyzed on just corn and hay areas and one parameter analyzed for pasture. The parameter ranges were set through available data, literature, and suggestions from the SWAT User's Manual.

We computed "Individual Sensitivity", which we defined as the change in model output in response to change in a single parameter. The selected output variables included: the water balance, sediment erosion, and available calibration stations. Surface water runoff, snowmelt, groundwater flow, evapotranspiration, and sediment yield were analyzed on a basin wide basis. The remaining six output variables chosen were location specific and were selected on the basis of the available calibration stations. These calibration stations included four flow stations and two sediment-loading stations (see Figure 2).

Calculating Sensitivity Index

The sensitivity indices for each output variable are computed from model simulations. A sensitivity index normalizes the response in the model output in comparison to changes in other parameters or output variables. This normalization facilitates comparison the effects of one parameter value perturbation over another. A cumulative sensitivity index can then be computed based on a weighting among all the individual sensitivity measures.

Proposed Methodology

We have developed a methodology for calibration and sensitivity analysis. The goal is to develop improved and computationally more efficient analysis methods that can be used to move from environmental field data (that are spatially and temporally distributed) and laboratory data to a model-based analysis that can be used to make improved forecasts, understand the effects of parameter values on model output, and to quantify the uncertainty associated with current and future events including weather

Our experience with calibration and sensitivity analysis in combination with separate research on optimization algorithms leads to the suggestion that the following is a reasonable approach utilizing data and models in water resources. The proposed methodology consists of the following Steps. The text in italics indicates the algorithm procedure and the normal text is a discussion of the algorithm.

STEP 1: *Select an initial value of the model parameters*. Many models are provided with default values of the parameters.

STEP 2: *Determine which of these parameters you want to consider changing to fit the data. Assume this number of parameters is K_1.* For each of these values, pick a minimum and maximum allowable value (which can be from the literature or preferably based on information for the site to which the model will be applied).

STEP 3: *Determine which output variables we want to consider in the calibration.* The output variables for the Cannonsville Watershed were described above and are typical for watershed model. Other applications could have other types of output variables. For example with groundwater remediation, output variables that are appropriate include the total time required to remediate a contaminated aquifer or the amount of contamination leaving a remediation site.

STEP 4: *Do a "hand calibration of the model parameter values to observed data to get an initial estimate of the best sets of parameter values.* Most models involve hand calibration, but we suggest that the entire process by spending only a short time on Step 4 to see if Step 5 and Step 6 can identify better calibration solutions more quickly than is possible with hand calibration.

STEP 5: *Let i=1. Perform the robust sensitivity analysis proposed in Benaman and Shoemaker (2003) to select the K2 most important* parameters.

RESULTS

Table 1 shows the selection of output variables to be considered, Table 2 shows the weights given to different output variables. Table 3 shows the ranking of parameter values given those weights on the output variables.

Table 1 Output Variables Chosen for Sensitivity Analysis

Output Variable	Summarized	Possible Influence
Surface water runoff Snowmelt Groundwater flow Evapotranspiration Sediment yield	Average annual value over entire simulation period	Basinwide management
Flow at Beerston (USGS Gauge #01423000) Flow at Trout Creek (USGS Gauge #0142400103) Flow at Little Delaware River (USGS Gauge #01422500) Flow at Town Brook (USGS Gauge #01421618) Sediment load at Beerston Sediment load at Town Brook	Monthly average over entire simulation	Calibration/in-stream processes

Table 2 Weighting Distributions (β_m) Selected for Sensitivity Analysis

	Weighting Method			
Output Variable	**A. Equal Weight**	**B. Focus on Beerston**	**C. Focus on Calibration***	**D. Focus on Basinwide Management**
Surface water runoff	0.091	0.125	0.0	0.125
Snowmelt	0.091	0.0714	0.0	0.125
Groundwater flow	0.091	0.0714	0.0	0.125
Evapotranspiration	0.091	0.0714	0.0	0.125
Sediment Yield	0.091	0.125	0.0	0.5
Flow @ Beerston	0.091	0.125	0.437	0.0
Flow @ Trout Creek	0.091	0.0714	0.026	0.0
Flow @ Town Brook	0.091	0.0714	0.018	0.0
Flow @ Little Delaware River	0.091	0.0714	0.065	0.0
Sediment load @ Beerston	0.091	0.125	0.437	0.0
Sediment load @ Town Brook	0.091	0.0714	0.018	0.0

- *β_m for this case is equal to subwatershed area of gauge/total area considered in sensitivity analysis*

Table 3 Each parameter was subject to two perturbation methods and two sensitivity indices (e.g. 4 cases). The percentages below are how often among these 4 cases was the parameter in the top 20 parameters. Hence if the parameter has a 100%, it means in all possible combinations of perturbation methods and sensitivity indices, the parameter was always in the top 20 parameters. More emphasis should be placed on parameters that are important for many weights (i.e. in many columns) and for many combinations of perturbation method and sensitivity indices.

	Percentage of times in the 'Top 20'			
	Weighting Method A	**Weighting Method B**	**Weighting Method C**	**Weighting Method D**
	All Equal Weights	**Focus on Beerston**	**Focus on Calibration**	**Focus on Basinwide Management**
APMBASIN	100	100	100	100
BIOMIXBASIN	100	100	100	100
CN2CSIL	100	100	100	100
CN2FRSD	100	100	100	100
CN2PAST	100	100	100	100
RSDCOPAST	100	100	100	100
SLSUBBSNBASIN	100	100	100	100
SMFMNBASIN	100	100	100	100
T_BASEPAST	100	100	100	100
T_OPTPAST	100	100	100	100
USLEKNY129	100	100	100	100
ESCONY129	100	75	75	100
SMTMPBASIN	100	75	75	100
LAT_SEDBASIN	100	50	100	100
CN2HAY	75	75	75	75
ESCONY132	75	75	75	50
GWQMNBASIN	75	75	75	75
TIMPBASIN	75	50	75	75
BIO_MINPAST	75	50	50	75
ROCKNY132	75	25	50	50
REVAPMNBASIN	50	50	50	75
ROCKNY129	50	25	50	25
USLEPCSIL	25	25	50	25
HVSTICSIL	25	25	25	50
USLECPAST	25	25	25	25
SMFMXBASIN	25	0	0	50
GSIPAST	0	0	25	0
ROCKNY026	0	0	25	0

CONCLUSIONS

Models arising in water resources and hydraulics can have a large number of parameters and a large number of data are available for calibrating the model. The techniques described in this presentation describe computationally efficient ways for improving calibration and sensitivity analysis. The method is robust in that it evaluates results in terms of alternative ways of perturbation, sensitivity indices and model outputs. The number of simulations required is 2*(number of parameters)*φ, where φ is the number of perturbations methods used. Φ is two in the numerical results used here, but φ could be 1 if the model is expensive to simulate. The number of output variables and number of different weights has a negligible effect on computation time assuming the simulation takes at least one minute and is even more neglibible for simulation times that are longer.

This approach can be used as a stepping stone to uncertainty analysis since it identifies the parameters that should be considered in both combined sensitivity analysis (i.e. looking at effects of uncertainties in combinations of parameters) and in uncertainty analysis involving stochastic methods like Monte Carlo Simulation or response surfaces.

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